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Procedia CIRP 56 (2016) 50 – 54

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9th International Conference on Digital Enterprise Technology - DET 2016 – "Intelligent Manufacturing in the Knowledge Economy Era"

Key Quality Characteristics Identification Method for Mechanical Product

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Abstract

All quality characteristics(QCs) need to be constantly tested in the process of mechanical parts machining. The efficiency is low and the cost is high. Therefore, the key quality characteristics(KQCs) identification is helpful for narrowing the scope of inspection and improving the detection efficiency. Aiming at this problem, this paper puts forward Mahalanobis-Taguchi System(MTS) method based on ReliefF algorithm. The main steps are as follows: (1)calculate the weigh of each characteristics by applying ReliefF algorithm, and then eliminate irrelevant quality characteristics (2)find out mechanical parts' final KQCs by using the orthogonal table and Signal/Noise Ratio(SNR) of MTS. Finally, the paper introduces the application of this method by setting a mechanical shaft as an example. The example shows that the method can improve the efficiency of the identification of mechanical parts quality characteristics.

Keywords: Key Quality Characteristics, Mahalanobis-Taguchi System, Orthogonal Table;

1. Introduction

Product quality control(PQC) is closely related to the cost and efficiency of enterprise. The key quality characteristics play a decisive role in the process of PQC. Therefore, the study on products key quality characteristics identification is very important. KQCs can greatly affect the quality of products. Enterprises can reduce potential quality problems by controlling them[1].

The studies on KQCs have shifted from qualitative to quantitative, from design level to manufacturing level, from low dimension to high dimension. In product designing phase, KQCs are usually obtained by the house of quality according from quality function deployment(QFD). Tang, etc.[2] have made a thorough research on the subject. As to the study on identification in the manufacturing process, Boeing company[3] defined KQCs initially based on the degree of quality loss in the actual process of quality management. The domestic representative researches in recent years are as follows: He, etc.[4] proposed the method to extract KQCs based on the house of quality(HOQ). Based on artificial neural network(ANN) technology, Zhang, etc.[5] proposed the extraction model of complex mechanical and electrical products KQCs and the optimization model of KQCs in manufacturing process. Shen, etc.[6] proposed a quality feature selection method based on the sequential factor test which was used in discrete event simulation test. The KQCs identification in the manufacturing process can be summed up as reducing dimension. Feature selection[7] and feature extraction[8] are the most commonly used methods. Aiming to these two methods, Yan[9] used the Filter algorithms of feature selection to identify the key quality characteristics, he took the interrelation between the quality characteristics and the final qualities into account but ignored the mad among them. Aiming to solve the defects existing in Filter, Xie, etc.[10] introduced features clustering in data mining(DM), and they got the subsets of KQCs which have strong correlation and less mad. He, etc.[11] introduced Cost-sensitive into information gain (IG), and they proposed a new method to identify KQCs based on the data sets of complex

doi:10.1016/j.procir.2016.10.015

products with high dimensional imbalance. Li, etc.[12] proposed ReliefF-W. The feature selection algorithm which can effectively identify KQCs and keep the budget accuracy was based on ReliefF algorithm and Wrapper algorithm.

Feature extraction and feature selection are essentially about optimization. MTS is one of the important tools to optimize system. It also has the function of forecast and diagnosis. The new method of multiple system enriches feature selection that it makes up MTS in terms of effectiveness and efficiency. Foreign scholars such as Taguchi, etc.[13] introduced systematically about MTS and pointed out the advantages of it. Jugulum, etc.[14] made a preliminary comparison between MTS and ANN by using the test data about liver function. The results showed that the two methods had similar classification accuracy when sample was large but MTS had higher accuracy than ANN when sample was small. Hong, etc.[15] continued to study these two methods, and then found that the diagnosis of MTS was better than ANN when sample was small. Wang, etc.[16] by comparing MTS, discriminate analysis and step-by-step discriminate analysis found that MST had a good advantage in prediction, and there's no need for it to satisfy some assumptions. Moira, etc.[17] used MTS to choose the appropriate input and output variables for data envelopment analysis, the breakthrough improved the evaluation accuracy of enterprise management efficiency. Mahalakshmi, etc.[18] applied MST into the evaluation criteria of optimization when choosing the optimal position of aquatic products. Domestic scholars Li, etc.[19, 20] also studied the same method, they mainly concentrated on introducing the theory of MTS and the application of it in multi-class recognition and pattern recognition. Zeng, etc.[21] applied the theory of hyper ellipsoidal support vector machine (SVM) into the threshold value determination of MTS. They found that MTS had high discriminant accuracy, and they also used larger-the-better features of fuzzy robustness to optimize MTS. Song, etc.[22] applied MTS into product key quality characteristics identification. They proved the validity of it by using a actual case, at the same time, they pointed out some disadvantages in application.

Aiming at solving the strong correlation among variables of MTS and the defects of efficiency, this paper puts forward a new way which combines MTS and ReliefF algorithm to identify mechanical parts key quality characteristics based on summarizing the existing methods. At first, the weight of each feature is calculated by using the theory of ReliefF algorithm, then the features which make small contributions in characteristic index system are eliminated. All QCs realize the first round of dimension reduction in this way. Next, a survey form is built. SNR is calculated and the survey form is optimized by using MTS. In this way, the rest of QCs realize the second round screening. Traditional MTS doesn't take the strong correlations among multiple variables into account, this means it doesn't consider the condition that mahalanobis distance is hard to calculate. Aiming at the problem, in this paper, we adopt Mahalanobis-Taguchi-Gram-Schmidt which is not affected by strong correlations to calculate mahalanobis distance.

2. ReliefF algorithm

ReliefF algorithm is a classical Filter algorithm which modified according to Relief algorithm by I.Kononenko. As the measurement of final classification, ReliefF can obtain the weight of each quality characteristic. Greater the weight value shows that the quality is more important. So, all quality characteristics can be ranked by this method according to importance, and then the key quality characteristics can be identified. The specific method to calculate weight by using ReliefF algorithm are as follows:

The data set R is classified into C types according to labels $K_1, K_2, ..., K_m$. Each type is marked as R_k(k=1,2...c), that means they are marked as $R_1, R_2, ..., R_C$ accordingly. The proportion of R_k in order is P_k. M samples which are selected from the data set R randomly are marked as X_i (i=1,2...m). That means they are marked as $X_1, X_2, ..., X_C$ accordingly. Then the homogeneous "n" samples X_{ij} (j=1,2...n) which are the nearest to Xi are found from the data set R. Finally, the weight of each quality characteristic is calculated. The importance of the quality characteristics "A" can be expressed as the difference between two probabilities. Used in the weight calculation can be expressed as follows:

$$W(\mathrm{A}) = \sum_{i=1}^{m}[\sum_{k\neq k_j}\frac{\mathrm{P_k}}{1-P_k}\sum_{j=1}^{n}\frac{\mathrm{diff}\ (X_i,\ X_{ij})}{mn} - \sum_{j=1}^{n}\frac{\mathrm{diff}\ (X_i, X_{ij})}{mn}] \quad (1)$$

$$diff\,(\mathrm{X}_i, \mathrm{X}_{ij}) = \frac{|\mathrm{v}_i - \mathrm{v}_{ij}|}{\max(\mathrm{A}) - \min(\mathrm{A})} \quad (2)$$

In equation 1 and 2, v_i, v_{ij} show the value of X_i, X_{ij} in the corresponding quality characteristics. *max(A)* and *min(A)* represent the maximum and minimum of "A" in all samples. $diff(\mathrm{X}_i, \mathrm{X}_{ij})$ shows the fluctuations of the eigenvalue between two different samples.

The weight value of the final quality characteristics which is obtained by ReliefF algorithm belongs to the interval[-1, 1]. The quality has nothing to do with the final quality if the weigh value of a certain characteristic belongs to the interval [-1, 0]. In the process of key quality characteristics identification, irrelevant quality features will be eliminated.

3. Mahalanobis-Taguchi System

3.1. Mahalanobis distance

MST combines the mahalanobis distance in statistics with the taguchi method. It makes data dimension reduction come true. The similarity of two unknown sample sets which follow the same distribution. Characteristic variables in multivariate system often have correlations. The abnormal degree of samples is often measured by using mahalanobis distance. Considering the correlations between variables, mahalanobis distance of samples is modified with the number of variables. In Mahalanobis-Taguchi-Gram-Schmidt, the mahalanobis distance calculation formula is expressed as follows:

$$MD_j = \frac{1}{k}\left(\frac{u_{1j}^2}{s_1^2} + \frac{u_{2j}^2}{s_2^2} + \ldots + \frac{u_{kj}^2}{s_k^2}\right) \quad (3)$$

In equation 3, $j=1,2...n$. k is the quantity of variables, $u_{1j}, u_{2j},..., u_{kj}$ is the value of the jst element in orthogonal variable, $s_1, s_2,..., s_k$ is the standard deviation of the orthogonalization vector $U_1, U_2,..., U_K$.

3.2. The taguchi method

MTS mainly applies the orthogonal table and SNR of taguchi method. It can achieve the goals of optimizing system and predicting performance.

3.2.1. The orthogonal table

Orthogonal table is usually flagged as $L_n(t^c)$. "L" means orthogonal table, "n" is the number of rows, and it shows experience times, "t" is the level of various factors, "c" is the number of columns. The two important characters of orthogonal table are as follows:

Orthogonal table is a main tool of orthogonal design. It is a kind of special form which can discharge the primary and secondary factors and determine the optimal solution. Orthogonal table is usually flagged as $L_n(t^c)$. "L" means orthogonal table, "n" is the number of rows, and it shows experience times, "t" is the level of various factors, "c" is the number of columns. The two important characters of orthogonal table are as follows:
(a)The times of different numbers in each column that appear are equal.
(b)In any two columns, the occurrences of each pair is equal when two numbers in the same lines are considered as a ordered pair.

These two properties demonstrate the superiority of the orthogonal table with "homodisperse" and "orderliness", "homodisperse" makes test points representative and "orderliness" makes it easy to further analyze test points. The collocation of each factor in each level is balanced when using orthogonal table to arrange tests. MTS uses a orthogonal table with two levels and assigns the variables to different columns when identifying product key quality characteristics. Then, each line can generate a markov space. Level "1" indicates that the variable is involved in the formation of the markov space, and the level "2" indicates that the variable is not involved. The so-called markov space is a data set according to the mean number, the standard deviation and the correlation matrix of normal samples' each variable.

3.2.2. Signal/Noise Ratio(SNR)

SNR is a kind of scale to measure quality which raised by Taguchi. It is the ratio of signal power and noise power in theory. SNR is usually expressed as η. The value of η is larger, the product quality is more stable and the quality loss is smaller. In the method of MTS, SNR is applied to determine the effective variables and to measure system function. Usually, we consider μ^2/σ^2 as SNR in the measurement, "μ" is the average of quality characteristics, "σ^2" is the variance of samples. SNR is mainly divided into three categories, "larger-the-better" type, "nominal-the best" type and "smaller-the-better" type. When using MTS to identify the key quality characteristics, the calculation formula of SNR is as follows:

$$\eta = -10\lg\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{MD_i}\right) \tag{4}$$

In equation 4, MD_i is quality characteristics' markov distance of the i[st] abnormal conditions, n is the quality characteristic number of each orthogonal table that participates in a markov space.

4. The method to identify key quality characteristics

This section presents a new method which combined MTS with ReliefF algorithm to identify the KQCs of mechanical parts based on the analysis of Section 2 and Section 3. Concrete ideas are as follows: Firstly, quality data sets collected from mechanical parts are inputted. The weight value of each quality index by using ReliefF algorithm is calculated. A reasonable threshold is set. Quality indexes based on weight value are ordered. The qualities with small entropy weight are eliminated, and then the filtered data sets are obtained. Secondly, a measurement table by using MTS method is built, the markov distance of normal samples and abnormal samples are calculated, the validity of the measurement table by comparing the the average markov distance of two kinds of samples is verified. Thirdly, a orthogonal table is designed, the signal-to-noise ratio of level "1" and level "2" as well as the deviation between them are calculated respectively. The measurement table is optimized and the most optimal data set is obtained.

It is worth mentioning that the optimized measurement table can also forecast and diagnose systems. The numerical value of markov distance is smaller, the difference of the same quality features in different samples is smaller, and the sample is more normal. So, we can extend the observation time appropriately. If the numerical value of markov distance is large, that means the sample may be abnormal. We need to find out the specific problems and take corresponding measures.

5. Numerical example

We set a mechanical shaft from a model as an example to verify the effectiveness of identification with Mahalanobis-Taguchi System combining the entropy weight method. The parts drawing are as follows:

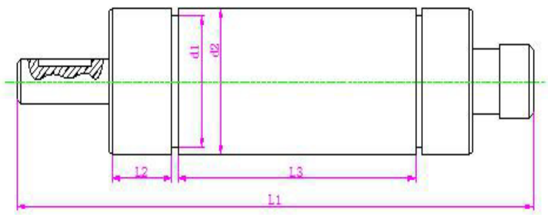

Fig.1. parts drawing.

Quality inspection personnel select 22 quality characteristics from 60 normal samples and 30 abnormal samples. The QCs are exterior length, total length L1, length L2, length L3, groove width and chamfering width, diameter d1, diameter d2, keyway length, keyway width and keyway depth, part quality, part volume, part surface area, density, surface hardness, surface roughness and case depth, straightness error, flatness error, cylindricity error and position degrees. They are in turn represented as X1, X2,... ,X22 for the identification of product key quality characteristics.

The first step is to obtain the weight of every quality characteristics according to formula 2. The results are shown in table 1.

Table 1. The weight of parts quality

QC	X1	X2	X3	X4	X5
weight	-0.321	0.112	0.091	0.086	0.045
QC	X12	X13	X14	X15	X16
weight	0.051	-0.284	-0.263	-0.132	0.035
QC	X6	X7	X8	X9	X10
weight	0.052	0.042	0.038	0.018	0.040
QC	X17	X18	X19	X20	X21
weight	0.030	0.062	0.069	0.053	0.052

To sort the weight of 22 quality characteristics from large to small are X2、X3、X4、X19、X11、X22、X18、X20、X21、X6、X12、X5、X7、X10、X8、X16、X17、X9、X1、X13、X14、X15. Among them, the weight of X1, X13, X14 and X15 are negative numbers. We can consider them as the irrelevant characteristics to final product quality and there is no need to repeatedly test them between two adjacent steps in the actual production process.

The second step is to obtain the Mahalanobis distance of other quality characteristics in normal and abnormal samples according to formula 3. The results are as shown in table 2 and 3.

Table 2. Mahalanobis distance of normal samples

Sample	1	2	3	4	5
MD	1.097	0.815	0.949	0.798	0.851
Sample	6	7	8	9	10
MD	0.880	1.114	0.708	0.931	0.831
MD	0.699	0.813	1.373	0.974	0.768
Sample	16	17	18	19	20
MD	1.042	0.868	0.909	0.792	0.620
Sample	21	22	23	24	25
MD	1.090	0.553	0.787	1.140	1.910
Sample	26	27	28	29	30
MD	0.856	1.112	0.399	0.905	0.744
Sample	31	32	33	34	35
MD	0.955	1.000	1.069	0.701	0.579
Sample	36	37	38	39	40
MD	0.706	0.669	0.651	0.747	0.569
Sample	41	42	43	44	45
MD	0.689	0.386	0.759	0.668	0.554
Sample	46	47	48	49	50
MD	0.810	0.865	0.693	0.899	0.511
Sample	51	52	53	54	55
MD	0.856	0.975	0.708	0.621	0.941
Sample	56	57	58	59	60
MD	0.681	0.733	0.924	0.491	0.535

Table 3. Mahalanobis distance of abnormal samples

Sample	1	2	3	4	5
MD	1.372	0.915	0.957	1.078	1.435
Sample	6	7	8	9	10
MD	1.369	1.469	1.129	1.389	1.035
Sample	11	12	13	14	15
MD	1.214	1.426	0.984	1.436	1.285
Sample	16	17	18	19	20
MD	1.245	1.024	1.161	0.967	1.273
Sample	21	22	23	24	25
MD	1.305	0.953	1.445	0.923	1.460
Sample	26	27	28	29	30
MD	0.966	1.265	1.131	1.311	1.434

In the above two tables, the average Mahalanobis distance in normal samples is 0.8045, while in abnormal samples is 1.0896. Most abnormal samples' Mahalanobis distances are larger than those in normal samples and the average Mahalanobis distances in normal samples is significantly greater than the average Mahalanobis distance in normal samples. These indicate that the measurement table is valid.

The third step is to select an orthogonal table of $L_{32}(2^{31})$ format, and calculate the SNR of each quality characteristic according to formula 4. And then use the SNR of level "1" minus the SNR of level "2" to calculate the difference between them and mark the result as η'.

Table 4. The difference of SNR between level "1" and level "2"

QC	X2	X3	X4	X5	X6	X7
η'	0.285	-0.034	0.347	0.828	0.413	0.187
QC	X8	X9	X10	X11	X12	X16
η'	-0.036	0.426	0.244	0.951	0.320	0.753
QC	X17	X18	X19	X20	X21	X22
η'	0.218	-0.077	-0.025	0.371	0.418	0.536
QC	X19	X20	X21	X22		
η'	-0.025	0.371	0.418	0.536		

Retaining the quality characteristics that SNR difference is a positive number, that's to say, excluding X3, X8, X18 and X19. After two screening, a total of 14 quality characteristics are left. To test the optimized inventory, the markov distance of 14 QCs in abnormal samples has turned into 0.9624 which is less than the original 1.0896. It shows that the optimized inventory is effective. Therefore, the final KQCs of parts are X2, X4, X5, X6, X7, X9, X10, X11, X12, X16, X17, X18, X20, X21, X22. Corresponding to the mechanical axis, the KQCs are the total length L1, length L3, groove width and chamfering width, diameter d2, keyway length, keyway width and keyway depth, part quality, surface hardness, surface roughness, case depth, straightness error, flatness error, cylindricity error and position degrees.

6. Conclusion

This paper forms a new method by introducing ReliefF algorithm into MTS method to identify mechanical parts key quality characteristics, and it sets the mechanical shaft of a model as an example to show that this method can effectively recognize KQCs. The new way cuts the quality characteristics from the original 22 to the final 16. However, this method still has its limits. On the one hand, when using ReliefF algorithm to screen the key quality characteristics, the eliminate parameters is determined by people. So, it exists considerable subjectivity. And on the other, how to set up the reasonable weight and how to further adjust the filter criteria. These will be the next direction of research.

Acknowledgements

We would like to acknowledge the support of the National Natural Science Foundation of the People's Republic of China (No. 51175322)

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